AI, firms and wages: Evidence from India

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August 21, 2023

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How is AI affecting services hiring in India?

- Progress in Artificial Intelligence (AI) could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Agrawal et al. 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)

- Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)

- Also critical for countries pursuing a services-led development model (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)

  ⇒ E.g. call centre operator vs. chatbot

- India is a key case: archetype of services-led growth; large + young popn.

  ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)

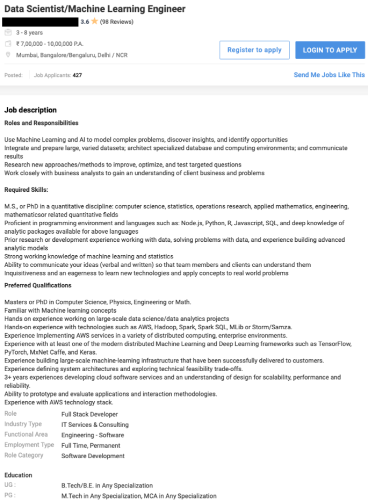
  ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on white-collar service sector jobs using vacancy posts from India's largest jobs website
  - ⇒ Measure establishment-level demand for AI skills and document a rapid take-off in AI demand from 2015
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies, as measured by patenting, to examine the impacts of AI adoption on non-AI jobs
- **What we find:**
  - ⇒ $\uparrow$1% in the AI vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-AI vacancy growth + $\downarrow$2.6pp in non-AI median wage offers over time
  - ⇒ The highest skilled occupations are worst affected, particularly managers & professionals
  - ⇒ AI reduces demand for 'intellectual' tasks such as those relating to analysis, projections and measurement
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects

Vacancy data from India's largest online job postings platform

- Platform hosts 60% of online job posts in India, we received anonymised 80% sample of posts across 2010-19
- Predominantly urban, full-time, formal white-collar services jobs
- 150k+ firms posted >1 one vacancy; average of 80 posts per firm
- Fields: job title, industry, role category, location, skills required, salary and experience ranges and educational requirements



Data Scientist/Machine Learning Engineer

[redacted] 3.6 ★ (98 Reviews)

3 - 8 years

₹ 7,00,000 - 10,00,000 P.A.

Mumbai, Bangalore/Bengaluru, Delhi / NCR

Register to apply | LOGIN TO APPLY

Posted: | Job Applicants: 427 | Send Me Jobs Like This

Job description

Roles and Responsibilities

Use Machine Learning and AI to model complex problems, discover insights, and identify opportunities
Integrate and prepare large, varied datasets; architect specialized database and computing environments; and communicate results
Research new approaches/methods to improve, optimize, and test targeted questions
Work closely with business analysts to gain an understanding of client business and problems

Required Skills:

M.S., or PhD in a quantitative discipline: computer science, statistics, operations research, applied mathematics, engineering, mathematicsor related quantitative fields
Proficient in programming environment and languages such as: Node.js, Python, R, Javascript, SQL, and deep knowledge of analytic packages available for above languages
Prior research or development experience working with data, solving problems with data, and experience building advanced analytic models
Strong working knowledge of machine learning and statistics
Ability to communicate your ideas (verbal and written) so that team members and clients can understand them
Inquisitiveness and an eagerness to learn new technologies and apply concepts to real world problems

Preferred Qualifications

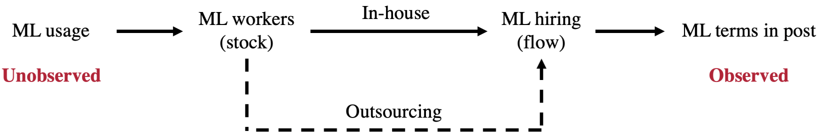
Masters or PhD in Computer Science, Physics, Engineering or Math.
Familiar with Machine learning concepts
Hands on experience working on large-scale data science/data analytics projects
Hands-on experience with technologies such as AWS, Hadoop, Spark, Spark SQL, MLib or Storm/Samza.
Experience Implementing AWS services in a variety of distributed computing, enterprise environments.
Experience with at least one of the modern distributed Machine Learning and Deep Learning frameworks such as TensorFlow, PyTorch, MxNet Caffe, and Keras.
Experience building large-scale machine-learning infrastructure that have been successfully delivered to customers.
Experience defining system architectures and exploring technical feasibility trade-offs.
3+ years experiences developing cloud software services and an understanding of design for scalability, performance and reliability.
Ability to prototype and evaluate applications and interaction methodologies.
Experience with AWS technology stack.

Role	Full Stack Developer
Industry Type	IT Services & Consulting
Functional Area	Engineering - Software
Employment Type	Full Time, Permanent
Role Category	Software Development

Education

UG :	B.Tech/B.E. in Any Specialization
PG :	M.Tech in Any Specialization, MCA in Any Specialization

Measuring demand for machine learning skills



- Classify a post as an AI vacancy if it includes words from list of specific AI terms (Acemoglu et al. 2021)
- Use demand for AI skills in vacancies to proxy for AI usage (Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)
- Exploit that primary method for sourcing AI capabilities is external hiring (McKinsey Global Institute 2019)

Assessing the types of tasks in AI job adverts

- Follow Michaels, Rauch and Redding (2018) in using a list of 1,665 English verbs and the meaning of verbs from Roget's Thesaurus, which classifies words according to their underlying concepts and meanings

- Roget's Thesaurus is organized into 6 classes, 10 divisions, 38 sections, and around 1,000 categories. Classes are:

  1. Abstract Relations: ideas such as number, order and time
  2. Space: movement, shapes and sizes
  3. Matter: the physical world and humankind's perception of it by means of the five senses
  4. Intellect: the human mind
  5. Volition: the human will and the human heart and soul
  6. Emotion, Religion, and Morality: the human heart and soul

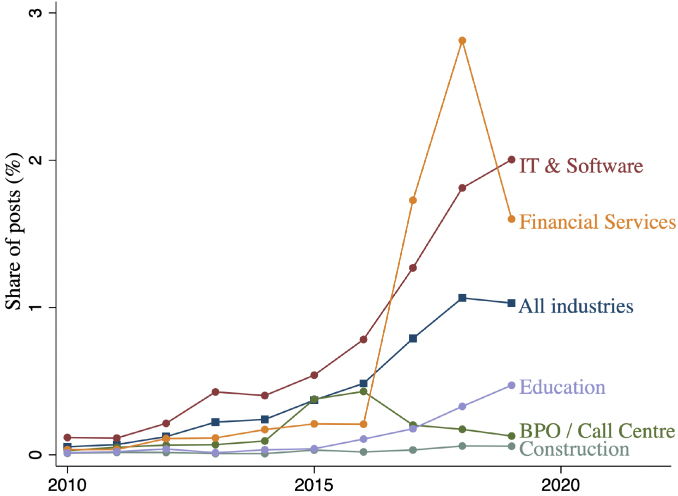
Most over-represented verbs in AI job ads

Extract the verbs in AI and non-AI job ads, then calculate the share of each verb relative to all verbs, and rank by difference in shares between AI and non-AI job ads:

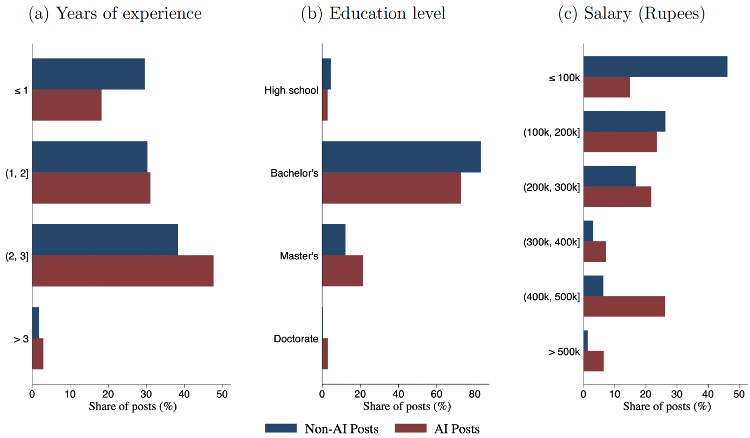
	Less likely to include	**More likely to include**
1	Call	Experience
2	Manage	Develop
3	Job	Build
4	Shift	Program
5	Plan	Design
6	Account	Work
7	Tar	Predict
8	Look	Deliver
9	Graduate	Use
10	Recruit	Advance

1. AI demand increased rapidly from 2015, particularly in IT, education and professional services

AI share of total posts, by industry



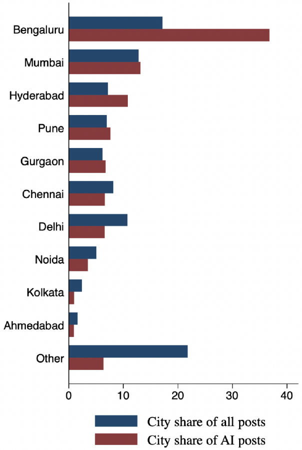
2. AI roles require more education, but offer substantially higher wages than other white-collar services jobs



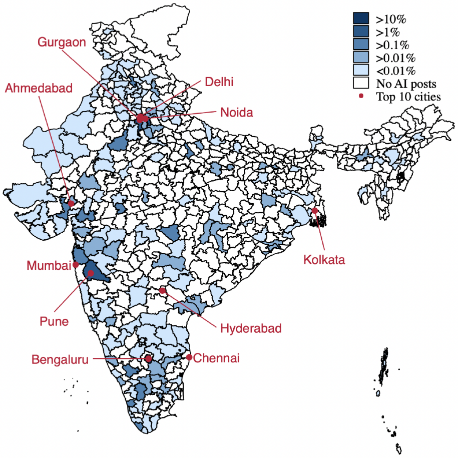
⇒ AI posts pay a 13% salary premium, even after controlling for education, experience, and detailed fixed effects (industry-region, industry-year, region-year, firm, occupation).

3. AI roles are highly concentrated in a few key technology clusters, particularly Bangalore

(a) Shares of posts across cities

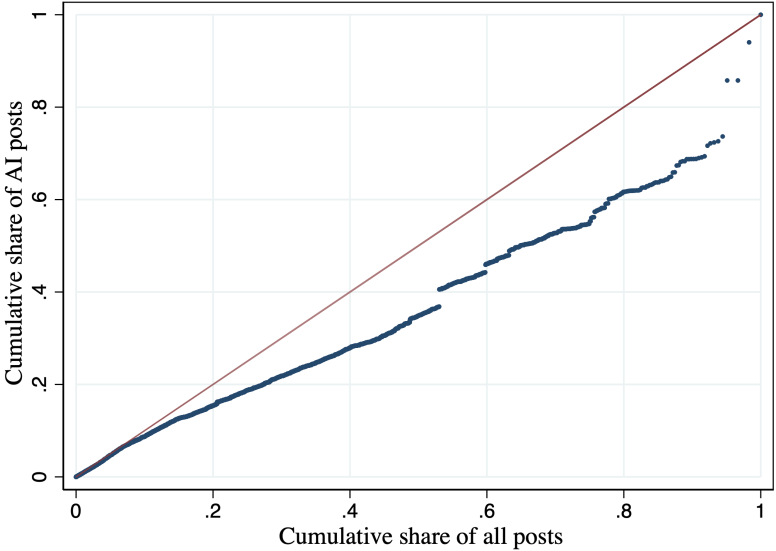


(b) Share of all AI posts, by city, 2010-2019

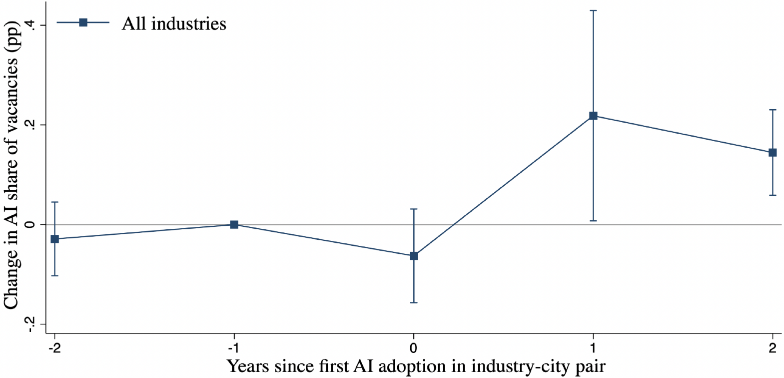


4. AI roles are highly concentrated in the largest firms

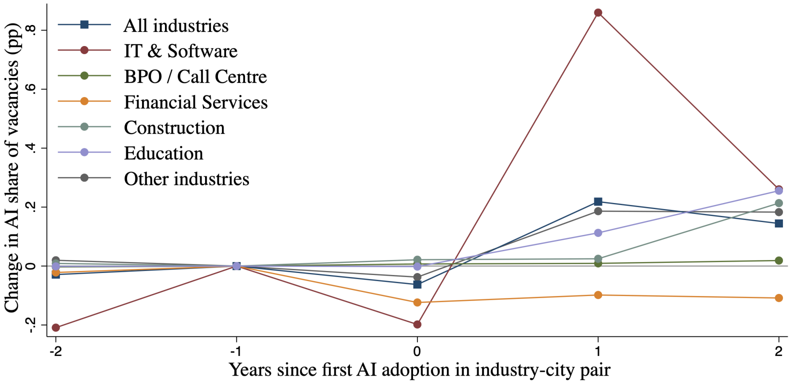
Distribution of AI posts across all firms, 2010-2019



5. Once one firm adopts AI, other firms in the same city and industry are more likely to adopt, over and above industry and region trends



5. Once one firm adopts AI, other firms in the same city and industry are more likely to adopt, particularly in the IT sector



Event study with propensity score matching

- In order to identify the impact of AI on employment and wages, we use an event study with AI adopters matched to non-adopters based on propensity scores (similar to Koch et al. (2021))
- AI adopters differ from non-AI adopters in that they are larger and pay higher wages. We run a Probit regression and construct propensity scores. Conditional on these propensity scores, treatment is orthogonal to establishment characteristics
- AI adoption leads to lower non-AI hiring

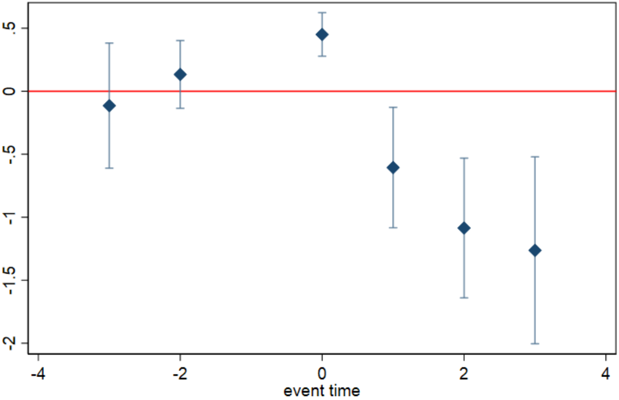
Event study with propensity score matching

- The event study regression is:

$$Y_{it} = \alpha_i + \beta_t + \sum_{k=-3\backslash-1}^{2} \gamma_k \mathbb{1}(K_{it} = k) + \gamma_{3+} \mathbb{1}(K_{it} \geq 3) + \epsilon_{it},$$

- where Y_{it} is the outcome, α_i and β_t are establishment and time fixed effects, K_{it} is the time difference between the current year and adoption of AI, ϵ_{it} is the error term, and the parameters γ_k are the outcomes of interest. We include 3 lags and leads, leaving out the first lead as is custom
- For the construction of propensity scores, we use the following variables:
  - lags of firmsize decile, hiring, median salary, 90th percentiles of salary and experience, firm age, salary dispersion, squared firmsize decile, standard deviation of experience, and interaction of standard deviation of salaries and firm age
- For employment, we need to account for non-hiring following adoption, and thus balance the panel. For wages, this imputation is not possible

AI adoption leads to reduced non-AI hiring



Two way fixed effects on a balanced panel. Similar results on region-year and industry-year levels. Results robust to using imputation estimator by Borusyak et al. (2021)

2SLS: *AI exposure* ⇒ *AI adoption* ⇒ *#Posts + Wage offers*

First stage:

$$\Delta Adoption_{fr,t-t_0} = \gamma \cdot Exposure_{fr,t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0} \quad (1)$$

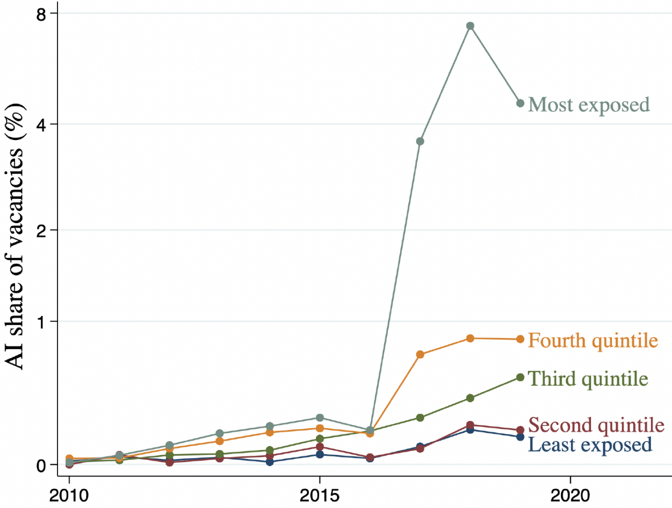
- We instrument demand for AI skills (our proxy for adoption) with Webb (2020) AI exposure measure

Second stage:

$$\Delta y_{fr,t-t_0} = \beta \cdot \Delta Adoption_{fr,t-t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0} \quad (2)$$

- Final sample: 2M vacancies from 25k establishments across 2010/12–2017/19
- Our primary unit of analysis are **firm-city pairs ('establishments')**; we cluster standard errors at the firm level and take IHS of *Adoption* and y
- Increasing the growth rate of AI demand by 1% between 2010-12 and 2017-19 (long difference) leads to a β **percentage point rise in the growth rate** of the outcome variable across the same time period

First stage: AI exposure predicts AI demand



A one s.d. rise in establishment AI exposure is associated with a 1.93% increase ($p < 0.01$) in growth rate of AI vacancies between 2010-12 and 2017-19.

Second stage: AI lowers growth in non-AI postings...

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.574***	-5.942***	-3.605***	-3.534***	-5.909***	-3.566***
	(1.168)	(1.624)	(1.139)	(1.166)	(1.624)	(1.137)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

A 1% increase in the establishment growth rate of AI vacancies results in a 3.6pp decrease ($p < 0.01$) in the growth rate of non-AI vacancies between 2010-12 and 2017-19, controlling for region, industry and firm size fixed effects.

Second stage: AI lowers growth in non-AI postings and total postings

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.574***	-5.942***	-3.605***	-3.534***	-5.909***	-3.566***
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Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

There is a similarly-sized decrease of 3.57pp in the growth rate of total vacancies
⇒ the negative effect on non-AI vacancies far outweighs the rise in AI vacancies.
Driven by incumbents.

Decline in demand hits higher-skilled occupations

Examine the impact on posts for particular categories of occupations:

	Growth in Non-AI Vacancies				
	Personal, sales & security	Clerks	Associate Professionals	Professionals	Managers
Growth in AI Vacancies	2.094***	1.092***	5.121***	-6.222***	-12.19***
	(0.487)	(0.354)	(1.252)	(1.581)	(2.632)
Fixed Effects:					
– Region	✓	✓	✓	✓	✓
– Industry	✓	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓	✓
First Stage F-Stat	27.17	27.17	27.17	27.17	27.17
Observations	22,251	22,251	22,251	22,251	22,251

Negative impact largest for corporate managers

Disaggregate the negative results for managers and professionals:

	Growth in Non-AI Vacancies					
	Professionals				Managers	
	Engineering Professionals	Health Professionals	Teaching Professionals	Other Professionals	Corporate Managers	General Managers
Growth in AI Vacancies	-4.951***	0.548*	0.284***	-2.687***	-12.18***	-2.403***
	(1.198)	(0.332)	(0.107)	(0.926)	(2.592)	(0.827)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓	✓	✓
First Stage F-Stat	27.17	27.17	27.17	27.17	27.17	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

Second stage: AI lowers median wage growth

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-2.703***	-3.101***	$\boxed{-2.599^{***}}$	-2.632***	-3.017***	-2.527***
	(0.799)	(0.895)	$\boxed{(0.758)}$	(0.770)	(0.862)	(0.730)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	25.32	25.64	26.39	26.61	26.84	27.71
Observations	22,064	22,064	22,064	22,071	22,071	22,071

Likewise, a 1% higher growth rate in AI vacancies between 2010-12 and 2017-19 reduces the growth rate of non-AI wage offers by 2.6 percentage points ($p < 0.01$).
Driven by incumbents.

Unpicking wage impacts

- Impacts on establishment-level median wages could be driven by:
  1. **Between occupation effects:** AI changing the occupational composition & where the median lies
  2. **Within occupation effects:** AI affecting wage offers for the same occupations
- Already showed that AI lowers growth in demand for the highest paid occupations & raises demand for the lowest paid

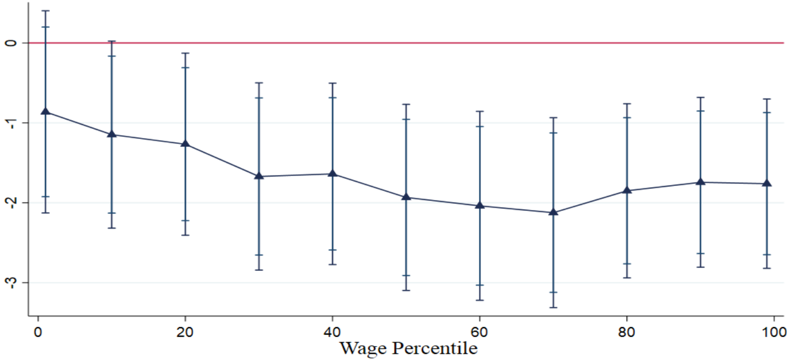
  ⇒ Between occupation effects

- Next explore impacts of AI on establishment wage offers for specific wage percentiles, then control for changing occupation shares. Finally, explore impacts of AI on occupation's median wage growth.

  ⇒ Also find within occupation effects

AI results in a downwards shift of the wage distribution...

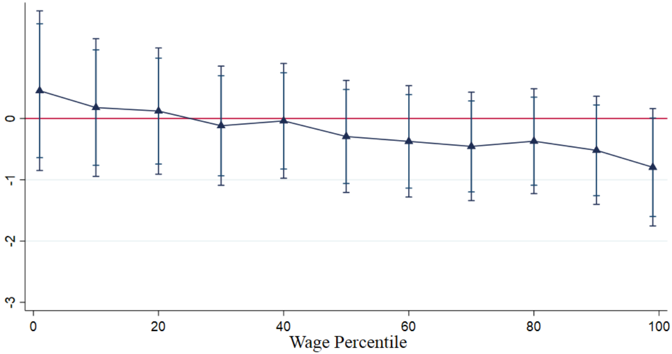
Impact of 1% higher establishment AI demand on non-AI wage growth:



Except for the lowest 10 percent of jobs, AI lowers the distribution of wage offers. Includes industry, firm decile, and region fixed effects, and controls for experience and education

...but holding occupational composition fixed, only top 1% see declining wage offers

Impact of 1% higher establishment AI demand on non-AI wage growth:

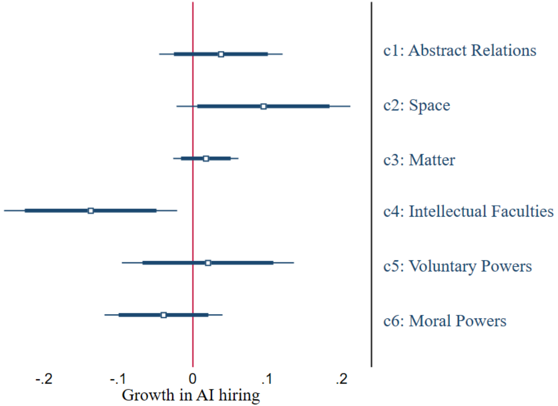


Controlling for changing occupation shares, we find a statistically significant effect on wage offers at the 10 percent level for the top 1 % highest paid roles. Includes industry, firm decile, and region fixed effects, and controls for experience and education

The task view: AI reduces demand for intellectual tasks

Evaluate the impact of AI on change in verb usage by verb class, using classification from Michaels, Rauch and Redding (2018) described above. Growth in AI hiring instrumented by baseline AI exposure according to Webb (2020).

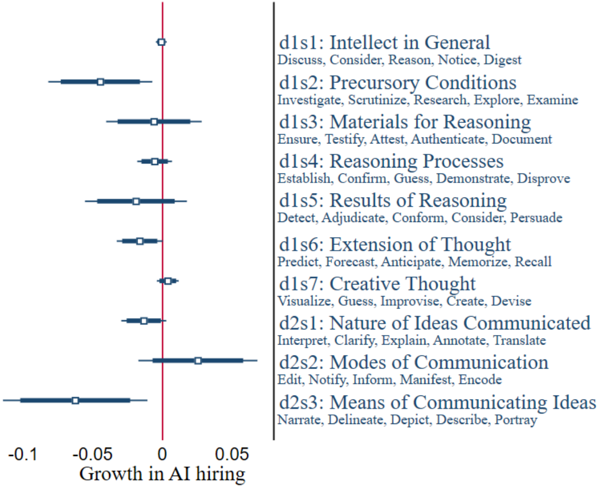
Impact of 1% higher establishment AI demand on verb usage by class:



Includes industry, firm decile, and region fixed effects.

The task view: AI reduces demand for intellectual tasks

Impact of 1% higher establishment AI demand on verb usage by section within Intellectual Faculties:



Includes industry, firm decile, and region fixed effects.

The task view: AI reduces demand for intellectual tasks

- Negative impacts on 'Intellectual Faculties' particularly strong for the sections of:
    - 'Precursory conditions and operations' e.g. account, analyze, check, classify, determine, discuss, distinguish, evaluate, gauge, inspect, proof, recognize, scrutinize, value, verify
    - 'Extension of thought' e.g. advise, announce, anticipate, forecast, memorize, predict, program, project, recognize, repeat, review
    - 'Means of communicating ideas' e.g. indicate, record, phrase, diffuse, digest, distribute, feature, measure, relate, review, view, write

Taking stock

⇒ AI results in changing labor demand *between occupations*: lower growth for higher skilled occupations & higher growth for lower skilled occupations alters the wage distribution

⇒ AI also results in declining wage offer growth *within* the top 1% highest paid job ads

⇒ AI lowers demand for intellectual tasks, for the full sample, and also within the 1% highest paid job ads

⇒ Declining wage offers for highest paid roles partially due to declining demand for tasks related to 'extension of thought', which command high wage premia within occupations

Baseline results are robust to:

1. Alternative exposure measure (Felten et al. 2018) ✓
2. Alternative baseline period (2013-15) ✓
3. Weighting by baseline establishment size ✓
4. AI adoption dummy instead of ihs-transformed AI hiring ✓
5. IHS robustness checks (Chen & Roth, 2022) ✓
6. Shift-share robustness checks (Goldsmith-Pinkham et al., 2020) ✓
7. Standard errors corrected for correlation following (Adão et al., 2019) ✓
8. Alternative data sources (NSS/PLFS, Prowess) ✓

Conclusion

Our paper:

⇒ Rich new data on AI demand and wage offers in a developing country

⇒ AI jobs pay a substantial wage premium, but they are highly concentrated in certain industries, cities and firms

⇒ Establishments reduce hiring and wages following AI adoption

⇒ AI adoption results in lower growth in postings and wages for non-AI roles + all roles

⇒ Displacement effects driven by high-skilled occupations and tasks relating to the use of 'intellect', such as analysis, projections and measurement

Key open questions:

⇒ **Key open question:** To what extent does AI adoption create new tasks & firms, and how do overall 'creative' vs. 'destructive' effects compare?

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Classifying AI posts

Back

Posts are categorised as AI-related if any of the following terms appear in either the ‘job description’ or ‘skills required’ fields:

Machine Learning, Computer Vision, Machine Vision, Deep Learning, Virtual Agents, Image Recognition, Natural Language Processing, Speech Recognition, Pattern Recognition, Object Recognition, Neural Networks, AI ChatBot, Supervised Learning, Text Mining, Support Vector Machines, Unsupervised Learning, Image Processing, Mahout, Recommender Systems, Support Vector Machines (SVM), Random Forests, Latent Semantic Analysis, Sentiment Analysis / Opinion Mining, Latent Dirichlet Allocation, Predictive Models, Kernel Methods, Keras, Gradient boosting, OpenCV, Xgboost, Libsvm, Word2Vec, Chatbot, Machine Translation and Sentiment Classification

(Acemoglu et al. 2021)

Probit regression for propensity scores

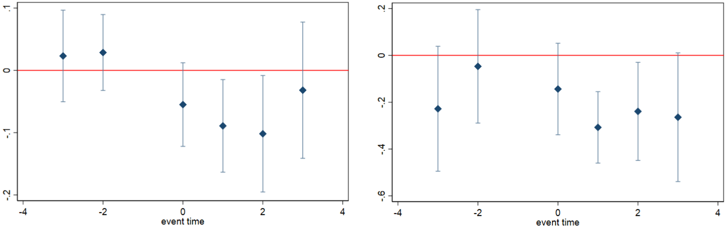
Back

	AI adoption
Lag of Firmsize Decile	-0.0125
	(0.0478)
Lag of Hiring	0.292***
	(0.0139)
Lag of Median Salary	0.111***
	(0.0210)
Lag of 90th Percentile of Salary	0.384***
	(0.0260)
Lag of 90th Percentile of Experience	-0.527***
	(0.0343)
Lag of Firm Age	0.0353***
	(0.00432)
Lag of Salary Dispersion	-0.000000584***
	(0.000000120)
Lag of squared Firmsize Decile	-0.00267
	(0.00347)
Lag of Salary Dispersion x Lag of Firm Age	7.96e-08***
	(1.71e-08)
Lag of Experience Dispersion	0.323***
	(0.0274)
Constant	-8.743***
	(0.310)
N	207,379

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

AI adoption leads to reduced non-AI hiring also on the level of regions and industries ◂ Back



Employment on region-year level (left) and on industry-year level (right) with two way fixed effects.

Instrument validity

Back

- Construct instrument from baseline occupation shares at the establishment level and their respective exposure to AI according to Webb (2020):

$$Exposure_{fr,t_0} = \sum_o PostShare^{t_0}_{fro} \cdot ExposureMeasure_o \tag{3}$$

- This is a Bartik approach: occupation shares measure exposure to a common shock. Identification – i.e. the validity of our instrument – is based on exogeneity of shares.
  - ⇒ AI shock occurred around 2015, with various technological innovations occurring only shortly beforehand – hence occupation shares in baseline plausibly exogenous with respect to the future shock.

- We can test for this following Goldsmith-Pinkham et al. (2020), who propose several validity checks by analogy with GMM and DiD:
  - ⇒ investigating correlates of shares
  - ⇒ examing pre-trends
  - ⇒ comparing different estimators and running over-identification tests

Test 1: Investigating correlates of shares

Back

- If baseline shares are correlated with other controls, the instrument could seem to have an effect which is instead properly attributed to the impact of the controls.
- Investigate extent to which baseline shares correlate with baseline controls which could themselves affect hiring/wage offer trends. We regress the instrument on baseline controls (education, experience, and salary.)
- Not an issue for overall instrument. Correlates Some individual occupation shares warrant inclusion of controls, in particular experience.

Test 2: Examining pre-trends

Back

- Pre-trends: pick 2010-2012 as pre-period and ask whether exposure based on these shares predicts year-on-year growth differences after 2014, so 2010-2012 not contained in growth rates.
- Violation of assumption of no pre-trends invalidates our approach. We regress employment and wage growth on the instrument based on 2010-2012 shares.
- For instrument, find no pre-trends. Pre-trends

Test 3: Alternative estimators and over-identification tests

Back

- Next compare a range of estimators (OLS, a range of IV estimators, an ML estimator and a Fuller-like estimator) and run over-identification tests. Similarity of different estimators is reassuring for the validity of our approach, and over-identification tests allow to test the validity of over-identifying restrictions.
- Find some general evidence for misspecification. Alternative estimators
- Comparing alternative estimators suggests validity of instrument for wages; so do misspecification tests. Both less favourable for employment results.
- Over-identification tests usually reject null of validity of over-identifying restrictions.
- Overall summary: lack of pre-trends, alternative estimators, and misspecification tests support Bartik instrument for wages, but less for employment.

Test 1: Correlates

Back

VARIABLES	(1) Instrument	(2) Instrument
Share of Highschool Education	-0.166	-0.166
	(0.204)	(0.204)
Share of Undergraduate Education	-0.232	-0.232
	(0.204)	(0.204)
Share of Postgraduate Education	-0.221	-0.221
	(0.204)	(0.204)
Mean Salary	4.86e-09	4.86e-09
	(4.34e-09)	(4.34e-09)
Mean Experience	-0.00217	-0.00217
	(0.00355)	(0.00355)
Constant	0.635***	0.635***
	(0.204)	(0.204)
Observations	22,201	22,201

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- Baseline controls (education, experience, salary) do not correlate significantly with the overall instrument.

Test 2: Pre-trends

Back

	Growth in Non-AI Vacancies				Growth in Non-AI Median Wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.000223	0.00617	0.00477	0.00622	0.0106	0.0272	0.0283	0.0275
	(0.0112)	(0.00599)	(0.0107)	(0.00602)	(0.0271)	(0.0175)	(0.0270)	(0.0177)
Fixed Effects:								
– Region		✓	✓	✓		✓	✓	✓
– Industry		✓		✓		✓		✓
– Firm Decile			✓	✓			✓	✓
Observations	296,730	296,730	296,730	296,730	296,730	296,730	296,730	296,730

Test 3: Alternative estimators and over-identification tests

Back

- Following Goldsmith-Pinkham et al., we compare Bartik to OLS, over-identified TSLS, using each share as a separate instrument, the Modified Bias-corrected TSLS (MBTSLS) estimator, the Limited Information Maximum Likelihood (LIML) estimator, and the HFUL estimator.
- Similarity in results between HFUL and LIML on the one hand, and MBTSLS and over-identified TSLS on the other hand supports the validity of our instrument.
- Bartik estimates are similar to LIML estimates when including establishment controls. Results from HFUL and MBTSLS are also similar, further supporting our instrument. The comparison of alternative estimators suggests validity of our instrument as we find estimates to be quite similar.
- We then run over-identification tests for the HFUL, LIML, and over-identified TSLS estimators, where the null hypothesis is the validity of the over-identifying restrictions. These tests do not reject the null hypothesis when including controls.
- For misspecification tests, we test whether Bartik is sensitive to the inclusion of controls. Similarity in estimates would support our instrument, and indeed we find support for our instrument's validity.

Shift-share robust standard errors

Back

Second stage: Impact of AI adoption on establishment non-AI vacancies. Adão, Kolesár, and Morales (2019) standard errors, correcting for correlated standard errors.

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.574**	-5.942*	-3.605**	-3.534**	-5.909*	-3.566**
	(1.666)	(3.436)	(1.479)	(1.663)	(3.437)	(1.475)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

IHS Robustness Checks

Back

- Our results are robust to other approaches and do not hinge on the IHS transformation. Following Chen & Roth, 2022, we show results from several robustness checks:
  - As the independent variable, we use an AI adoption dummy in order to circumvent the issue of estimates' scale sensitivity. Our first set of robustness results winsorizes outcomes in levels at the 5% and 10% levels.
  - We also turn the dependent variables into binary outcomes for exceeding a threshold, e.g. the median.
  - Finally, regress changes in log(1+x) of AI hiring, instrumented by AI exposure, on changes in log(1+x) of vacancies and wages.
- Our findings survive all these tests, the results of which are available on request.

Firm-level employment results

Back

We study the establishment level, as geographical
variation matters, and the firm-level does not allow us to include region fixed effects.

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.456**	-4.353	-1.193	-1.461**	-4.369	-1.200
	(0.688)	(2.678)	(0.749)	(0.691)	(2.690)	(0.752)
Fixed Effects:						
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	16.51	4.16	12.01	16.51	4.16	12.01
Observations	6,785	6,785	6,785	6,785	6,785	6,785

Firm-level wage results

◂ Back

We study the establishment level, as geographical
variation matters, and the firm-level does not allow us to include region fixed effects.

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.276	-0.860	-0.340	-0.273	-0.856	-0.337
	(0.234)	(0.621)	(0.287)	(0.233)	(0.617)	(0.285)
Fixed Effects:						
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	16.56	4.172	11.88	16.71	4.226	11.99
Observations	6,764	6,764	6,764	6,766	6,766	6,766

Baseline results driven by ‘incumbents’, not ‘startups’

Employment results for startups Back

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-8.088	-17.32	-8.887	-8.053	-17.32	-8.853
	(7.710)	(13.90)	(7.827)	(7.741)	(13.96)	(7.858)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	2.637	2.469	2.801	2.637	2.469	2.801
Observations	21,085	21,085	21,085	21,085	21,085	21,085

Baseline results driven by 'incumbents', not 'startups'

Employment results for incumbents

Back

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.043***	-2.530**	-2.998*	-3.035***	-2.520**	-2.983*
	(1.146)	(1.027)	(1.808)	(1.150)	(1.030)	(1.811)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	24.51	24.33	7.454	24.51	24.33	7.454
Observations	17,348	17,348	14,729	17,348	17,348	14,729

Baseline results driven by ‘incumbents’, not ‘startups’

Wage results for startups

Back

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-9.946*	-11.88*	-9.754*	-12.26	-14.77	-11.93
	(5.697)	(6.913)	(5.478)	(8.323)	(10.31)	(7.880)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	4.131	4.12	4.326	2.668	2.558	2.837
Observations	20,934	20,934	20,934	20,959	20,959	20,959

Baseline results driven by 'incumbents', not 'startups'

Wage results for incumbents Back

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.781***	-1.813***	-4.630**	-1.824***	-1.858***	-4.645**
	(0.622)	(0.619)	(1.926)	(0.640)	(0.638)	(1.931)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	25.58	7.519	24.48	24.35	7.529
Observations	17,259	17,259	14,648	17,266	17,266	14,652